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Evaluating Water Withdrawals for Regional Water Management Under a Data-driven Framework

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Abstract: With an increase in population and economic development, water withdrawals are close to or even exceed the amount of water available in many regions of the world. Modelling water withdrawals could help water planners improve the efficiency of water use, water resources allocation, and management in order to alleviate water crises. However, minimal information has been obtained on how water withdrawals have changed over space and time, especially on a regional or local scale. This research proposes a data-driven framework to help estimate county-level distribution of water withdrawals. Using this framework, spatial statistical methods are used to estimate water withdrawals for agricultural, industrial, and domestic purposes in the Huaihe River watershed in China for the period 1978–2018. Total water withdrawals were found to have more than doubled, from 292.55 × 10^8 m^3 in 1978 to 642.93 × 10^8 m^3 in 2009, and decreased to 602.63 × 10^8 m^3 in 2018. Agricultural water increased from 208.17 × 10^8 m^3 in 1978 to 435.80 × 10^8 m^3 in 2009 and decreased to 360.84 × 10^8 m^3 in 2018. Industrial and domestic water usage constantly increased throughout the 1978–2018 period. In 1978, industrial and domestic demands were 20.35 × 10^8 m^3 and 60.04 × 10^8 m^3, respectively, and up until 2018, the figures were 105.58 × 10^8 m^3 and 136.20 × 10^8 m^3. From a spatial distribution perspective, Moran's *I* statistical results show that the total water withdrawal has significant spatial autocorrelation during 1978–2018. The overall trend was a gradual increase in 1978–2010 with withdrawal beginning to decline in 2010–2018. The results of Getis-Ord G_i^* statistical calculations showed spatially contiguous clusters of total water withdrawal in the Huaihe River watershed during1978–2010, and the spatial agglomeration weakened from 2010 to 2018. This study provides a data-driven framework for assessing water withdrawals to enable a deeper understanding of competing water use among economic sectors as well as water withdrawal modelled with proper data resource and method.

Keywords: water withdrawal; data-driven framework; spatial data analysis; water coefficient; Huaihe River watershed, China

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1 Introduction

Population growth and economic development are placing unprecedented pressure and challenges on global water resources due to the scarcity of freshwater increasingly becoming a threat to human society in many

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parts of the world. This is especially true given the effects of climate change (Kummu et al., 2016; Liu et al., 2017; Wongso et al., 2020), e.g., floods and droughts, and seasonal-induced water shortages (Yang et al., 2018). Most countries around the world are facing freshwater shortages for domestic, industrial, and agricultural purposes, and in particular for agricultural irrigation needed to grow more food for increasing populations, especially in the Middle East and North Africa. Results from Mekonnen and Hoekstra reported that there were four billion people living under conditions of severe water shortage, mainly in developing countries such as India and China (Mekonnen and Hoekstra, 2016). Another study showed that approximately 25% of global farmland, responsible for feeding 840 million people, is affected by scarce water resources due to inadequate institutional and economic determinants, such as imperfect policies for water withdrawals, the long-term economic lagging and economic disparities, and ineffective mechanism to overcome transboundary water-withdrawal conflicts between upstream and downstream (Rosa et al., 2020).

With increasing global water demand, policies for economic growth and social development must consider the restriction and influence of water resources on the socio-economic system. Numerous papers and reports on sustainable development and utilization of water resources have been published, ranging from climate impact to human activities, including the constraints of population, economic growth, water-use efficiency, and technological change (Jia et al., 2004; Zhang et al., 2009; Kummu et al., 2016; Ren et al., 2020; Zhu et al., 2020). Further research has been carried out from the perspective of the water cycle. With the omission of evaporation, precipitation from the atmospheric cycle results in surface runoff (blue water for human consumption) and replenishment of underground water supplies and soil moisture (green water for vegetation). The blue water supply has become important for industrial, agricultural, domestic, and environmental purposes. Climate change and human water use have become key factors in controlling the balance between water supply and water demand. Besides the impact of climate change on water supply (Gosling and Arnell, 2016; Tian et al., 2020b; Liu et al., 2021), efficient management of water resources is also considered to be a significant determinant in the effective utilization and allocation of water resources among different water use sectors, and to help alleviate water shortages both in the present and the future.

Policymakers at all levels urgently need information about how much water has been or is being consumed/demanded by households, economic activities, and in the ecosystem, especially on a regional or local level. These data are important for helping to improve and implement effective water resources management. Various studies from the past have explored how water management might affect global, continental, or local water demands in agricultural, industrial, and domestic sectors in the present and future (Hook, 1994; Liu et al., 2017; Joseph et al., 2020; Tian et al., 2020a). Particularly in earlier times, the quantity of water use/withdrawal has not been measured and recorded for various economic activities and therefore, is unallocated according to market mechanisms, meaning that it is very difficult to quantify water productivity as with capital or labor in the economic models (Boero and Pasqualini, 2017). To trace the flow paths of water withdrawals in socio-economic systems, scholars have developed various indirect methods to help detect the impacts of human activities on water withdrawals. This research has been conducted using water withdrawal quantities from industrial, agricultural, and domestic activities (Wang et al., 2004; Luan and Liu, 2017; Zhang et al., 2020a). For industrial and domestic water demands, the water coefficient, water use/withdrawal per outcome such as gross domestic product (GDP) or population, is used widely to model present and future water use in industrial sectors, such as the manufacturing and electric power industries on a local, regional, and global scale (Van Vliet, 2016; Fujimori et al., 2017). By comparison, it is more complicated to be able to simulate agricultural water demand because of different data sources and models. Agricultural water demand can be estimated using various methods such as the water coefficient, the Penman-Monteith formula, the water footprint, and the remote sensing technique (Wisser et al., 2008; Mekonnen and Hoekstra, 2011; Hoekstra and Mekonnen, 2012; D'Odorico et al., 2020; Yousaf et al., 2021). Therefore, findings are varied owing to different research methods used for different purposes in the same study area.

Aside from modelling water withdrawals as a result of human activities that use blue water, another popular research topic is to create a model of the virtual water that has been consumed directly by agricultural and industrial goods or products activity through local-, national- or global-scale trade (Graham et al., 2020; Lowe et al., 2020; Qian et al., 2020; Zhuo et al., 2020). These studies also attempted to trace the spatial flow and quantity of virtual water amongst different products, mainly from the agricultural and industrial sectors, to help with decision-making for sustainable water use. In addition, a detailed review has been conducted on the methods for modelling water withdrawal or water use at a continental-to-global scale (Joseph et al., 2020). These methods include WaterGAP (Water-global Assessment and Prognosis) (Döll et al., 2012; Chen et al., 2020) and CROPWAT (Crop Water Requirement) (Döll and Siebert, 2002) models, which were used to compute water use in various economic sectors for each country studied. Although many studies have also been conducted on water demand on a global scale while assessing water scarcity, data for modelling water use at this scale can only be focused on several easily available indicators, such as population and GDP (Kummu et al., 2010; Distefano and Kelly, 2017). Detailed long-time series socio-economic factors influencing the estimation of water demand can not be obtained at a local scale because these indicators have not been included in a census or have been recorded at different times at county-level only. The lack of local data is particularly prevalent in developing countries and regions, such as Latin America, India, China, and Africa. As a result, the long-term temporal and spatial variations of water withdrawals have been partly ignored at the medium and lower levels such as regional or watershed levels. On the other hand, the findings on a larger scale can not provide scientific advice to local governments to help improve water management as they can not implement suggested water plans according to these findings. The reason is that local water management needs the information about water withdrawals, population, and GDP on a detailed or local scale, e.g., county-level, in the present to make highly operational scheme of water resources allocation among different economic sectors in the future. Then, the efficiency of water management can be improved or achieved, which is an important way for adapting strategies for water management at local governments (Cosgrove and Loucks, 2015; Iglesias and Garrote, 2015).

Regional socio-economic data are key factors to estimate water withdrawal, especially when relevant statistical data for water withdrawal cannot be available. A data-driven framework for various data sources and simulation methods is needed to propose to reliably assess water demand to make optimal decisions for local sustainable water management. Under this framework, the outcomes of modelling water demand are crucially important for water planners from governments at all levels and water users from various industrial sectors. This study provides a bridge between water management practices and water resources science and assists in the better integration of water science and management practices. Consequently, the purpose of this paper proposes a data-driven framework to detect the spatio-temporal distribution of water withdrawals at a county level in the Huaihe River watershed in China during 1978–2018. Our findings will also provide more detailed water withdrawal data to help create policies which will be more easily implemented, and to properly allocate water resources and thus improve watershed management.

2 Study Area and Methodologies

2.1 Study area and data processing

The chosen area (30°57′39″N–36°19′18″N, 111°53′27″E–121°22′55″E) in this study is the Huaihe River watershed in China (Fig. 1). The region is intensively cultivated and covers an area of about 26.88 × 10^4 km^2. The west, southwest and north of the basin are mountainous and hilly (about 33%), and the rest comprises vast plains (approximately 67%). The Huaihe River watershed is in the transition zone between the humid and semi-arid climates in China which has an extreme monsoon season (Wu and Yan, 2013; Gao et al., 2014). The annual precipitation varies considerably with a mean annual precipitation of 920 mm which mainly occurs from June to September, accounting for 50%–80% of the total annual precipitation, while the precipitation in the other months is less than 10% of the whole year's precipitation. The average annual temperature is 13.2–15.7 °C in the Huaihe River watershed, which increases from north to south with the hottest monthly temperature (usually in July) around 27 °C, and the coldest temperature (in January) around 0 °C.

The Huaihe River watershed spans most of five

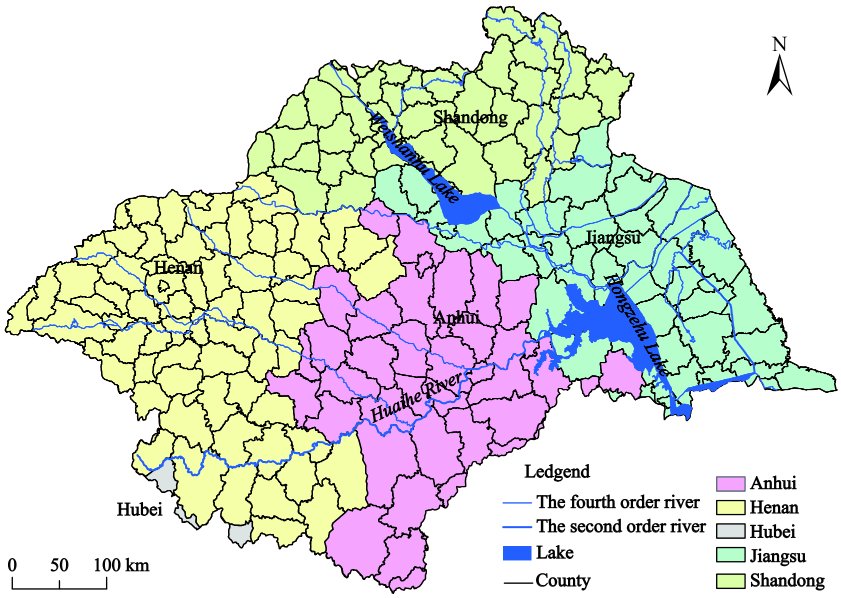

Fig. 1 The geographical location of the Huaihe River watershed, China

provinces including Henan, Anhui, Jiangsu, Shandong, and Hubei. It includes 212 counties (based on China Administrative Divisions 2005) with an average density of 539.62 people/km^2 in 1978 and 824.30 people/km^2 in 2018. In this watershed, the total GDP was 136.57 × 10^8 yuan (RMB) in 1978 and 48 779.98 × 10^8 yuan in 2018. Water withdrawals for agricultural, industrial, and domestic sectors were 376.35 × 10^8 m^3, 75. 81 × 10^8 m^3 and 76.00 × 10^8 m^3, respectively, in 2018 (The Huaihe River Commission of the Ministry of Water Resources of China, 2018). The reason for choosing this watershed as study area is that it is a region with severe water shortage. However, it is an important crop production base and needs a large amount of irrigation water. There exists severe contradiction between water supply and demand. Therefore, research on the spatio-temperal distribution of water withdrawal in this watershed enables us to deeply understand water-use competition among economic sectors, and also provides time-series data on water withdrawal for water management plans.

Data for water withdrawals collected in this study are from the China National Water Census (http://www.mwr.gov.cn/sj/tjgb/szygb/), and China's Provincial Water Resources Bulletins (1995–2018) (https://data.cnki.net/). Time-series data for population, effective irrigation area, GDP, and other social-economic indicators are mainly from provincial and municipal statistical yearbooks (1978–2019) and a compilation of statistical data for 60 yr in Zhejiang, Hubei, Anhui, Henan, and Shandong provinces (http://data.cnki.net.zzulib.vpn358.com/). Statistics for water withdrawals in the agricultural, industrial, and domestic sectors in China can only be traced back to around 1995, while water withdrawals were not recorded before 1994 by the Department of Water Resources at a county level. As a result, information on water withdrawals was not available for general water planning from 1978 to 1994. Unfortunately, the amount of water withdrawal for agricultural or industrial purposes has not been recorded by the Department of Water Resources at county level, so we cannot obtain spatio-temporal distribution of local detailed water withdrawals. Therefore, we have used interpolating methods for processing the missing data to make the time series of water withdrawals complete among different sectors (Dong and Peng, 2013; Little and Rubin, 2019). Provincial-to-county level data for water withdrawal per unit in the agricultural, industrial, and domestic sectors can be obtained for each province covered in the Huaihe River watershed during 1978–2018. To eliminate the impact of the price index on industrial production, it is calculated at comparable prices (price in 1978 = 100). We process the missing industrial production data for each county according to the regression relationship between industrial and secondary productions when the county-level data for industrial production is not available for the period 1978–2018. The county administrative unit in the Huaihe River watershed is based on the China Administrative Divisions 2005 (https://www.resdc.cn/data.aspx?DATAID=287). Statistical data at county level before 2005 and after 2005 were uniformly adjusted to the China Administrative Divisions 2005 for ensuring the consistency of data at county-level unit. Statistical data such as GDP and population in the boundaries of some counties intersecting that of the Huaihe River watershed were revised by multiplying the ratio between the covered area in this watershed and whole area of complete county.

2.2 Description of a data-driven framework for modelling water withdrawals

We extracted nearly 20 000 research articles and reviews whose titles contained keywords for 'water use', 'water requirement', 'water demand', 'water consumption' and 'water withdrawal' in the 'Web of Science' core collection database (www.webofscience.com/) for the period 1978–2020. These keywords mainly focused on related research areas including agriculture, engineering, environmental sciences, water resources, biodiversity conservation, geography, remote sensing, and urban studies (Estes et al., 1978; Rosegrant et al., 2000; Liu et al., 2017; Rosa et al., 2020). However, there is scanty information on the differences between these keywords when modelling water demand, which results in greater diversity among various water demand estimations when the outcomes of similar studies are compared (Joseph et al., 2020). This will not be beneficial to governments in making more informed water policy decisions and will expand the gap between theoretical results and local plans and policies for water development.

Therefore, a common data-driven framework is proposed here to model water withdrawals for various purposes using different data resources and models: 1) water requirement/demand herein is referred to calculate theoretical maximum demand amounts for agricultural, industrial, and domestic purposes in various time spans. For example, agricultural water demand can be estimated by remote sensing data or crop growth models (Joseph et al., 2020). Socio-economic indicators such as population and GDP are most commonly used to estimate water demand amongst water-dependent sectors (Flörke et al., 2013). These studies focus on the theoretical estimation of water demands in different socio-economic sectors at a global-to-national scale due to other detailed statistics not being available; 2) water withdrawal/use is the water that is delivered by water supply facilities to various sectors for different purposes, and meets corresponding water-quality levels (Wang et al., 2006), e.g., the Standard for Integrated Discharge Standard of Water Pollutions (DB11/307–2013) and the Standards for Irrigation Water Quality (GB5084-2005) in China. Corresponding statistical data from the Department of Water Resources of China can be obtained for some time-frames, and under this framework, an estimation of water withdrawal can be conducted with a water coefficient or other econometric methods, using available data on a regional or local scale; 3) water consumption, sometimes referred to as virtual water, is the volume of water consumed or embedded by agricultural/industrial products and services traded between importing or exporting nations or provinces (Liu et al., 2006; Deng et al., 2021). Econometric tools such as input-output analysis and life-cycle assessment are used commonly to estimate the quantities of water consumed through economic activities according to data for industrial or agricultural import and export trade (Pfister et al., 2009; Lenzen et al., 2013).

2.3 Water withdrawals modelling

We calculate water withdrawals for agricultural, industrial, and domestic sectors at county-level according to the second type of data-driven framework described in Section 2.2. Data for water withdrawals at province-level are obtained from the Department of Water Resources and the method chosen here is the water coefficient, which has been used often in water management departments or in water resources planning and allocation (Boero and Pasqualini, 2017; He et al., 2018).

(1) Water withdrawal at provincial level in the Huaihe River watershed

Missing data for water withdrawals in agricultural, industrial, and domestic sectors can be modelled at provincial level in Henan, Anhui, Shandong, Jiangsu and Hubei provinces covered in the Huaihe River watershed during 1978–1997, according to existing data for water withdrawal and socio-economic indicators from 1998 to 2018. For example, missing data for water withdrawals can be estimated in Henan, Shandong, Anhui, Jiangsu and Hubei provinces, listed in Table 1.

According to Table 1, complete time-series data for water withdrawal in each province can be available in the Huaihe River watershed from 1978 to 1997. Then, the water coefficient or water withdrawal per outcome

Table 1 Missing data for water withdrawals modelled in Henan, Shangdong, Anhui, Jiangsu and Hubei Provinces in China during 1978–1997

Province	Dependent variable	Independent variable	Model	*F* / Sig.	*t*	Sig.	*S.E.*
Henan	AWD (y)	FIRGDP (x)	$y = -7 \times 10^{-6} x^2 + 0.042x + 65.845$ ($R^2 = 0.869$)	26.415 / 0.000**	x (4.860)	0.000**	1.12%
					x^2 (–4.069)	0.001**	
					constant (6.847)	0.000*	
	IWD (y)	SECGDP (x)	$y = -1 \times 10^{-7} x^2 + 0.003x + 32.438$ ($R^2 = 0.887$)	62.487 / 0.000**	x (7.540)	0.000**	1.18%
					x^2 (–5.674)	0.000**	
					constant (18.391)	0.000**	
	DWD (y)	TOPOP (x)	$y = 0.836\exp(0.001x)$ ($R^2 = 0.881$)	125.8 / 0.000**	x (11.218)	0.000**	1.83%
					constant (2.892)	0.010*	
Shandong	AWD (y)	FIRGDP (x)	$y = 60.527\exp(0.001x)$ ($R^2 = 0.876$)	26.019 / 0.000**	x (6.235)	0.000**	0.66%
					x^2 (–6.683)	0.000**	
					constant (19.438)	0.000**	
	IWD (y)	SECGDP (x)	$y = 6 \times 10^{-8} x^2 - 0.002x + 47.578$ ($R^2 = 0.8128$)	18.613 / 0.000**	x (–5.841)	0.000**	2.93%
					x^2 (5.373)	0.000**	
					constant (15.304)	0.000**	
	DWD (y)	TOPOP (x)	$y = 77.915\ln(x) - 681.12$ ($R^2 = 0.839$)	28.354 / 0.000**	$\ln(x)$ (5.325)	0.000**	1.63%
					constant (–5.084)	0.000**	
Anhui	AWD (y)	FIRGDP (x)	$y = -3.1 \times 10^{-5} x^2 + 0.126x + 33.47$ ($R^2 = 0.833$)	16.514 / 0.000**	x (3.685)	0.003**	1.91%
					x^2 (–3.103)	0.009**	
					constant (1.276)	0.026*	
	IWD (y)	SECGDP (x)	$y = -6 \times 10^{-7} x^2 + 0.011x + 49.969$ ($R^2 = 0.888$)	58.453 / 0.000**	x (7.533)	0.000**	0.73%
					x^2 (–6.081)	0.000**	
					constant (10.918)	0.000**	
	DWD (y)	TOPOP (x)	$y = 0.350\exp(0.001x)$ ($R^2 = 0.962$)	306.763/ 0.000**	x (17.515)	0.000**	0.14%
					constant (3.922)	0.002**	
Jiangsu	AWD (y)	FIRGDP (x)	$y = -2 \times 10^{-5} x^2 + 0.108x + 151$ ($R^2 = 0.805$)	16.723 / 0.000**	x (5.328)	0.000**	1.09%
					x^2 (–4.968)	0.000**	
					constant (6.487)	0.000**	
	IWD (y)	SECGDP (x)	$y = -6 \times 10^{-7} x^2 + 0.015x + 92.624$ ($R^2 = 0.809$)	21.008 / 0.000**	x (3.279)	0.005**	1.88%
					x^2 (–2.710)	0.016*	
					Constant (3.85)	0.002**	
	DWD (y)	TOPOP (x)	$y = 0.629\exp(0.001x)$ ($R^2 = 0.9145$)	160.419 / 0.000**	x (12.666)	0.000**	0.72%
					constant (2.895)	0.011*	
Hubei	AWD (y)	FIRGDP (x)	$y = 14.752\ln(x) + 31.152$ ($R^2 = 0.619$)	30.902 / 0.000**	$\ln(x)$ (5.559)	0.000**	1.23%
					constant (1.587)	0.000**	
	IWD (y)	SECGDP (x)	$y = -5 \times 10^{-7} x^2 + 0.010x + 62.395$ ($R^2 = 0.879$)	21.654 / 0.000**	x (7.507)	0.000**	1.71%
					x^2 (–6.770)	0.000**	
					constant (16.138)	0.000**	
	DWD (y)	TOPOP (x)	$y = 3 \times 10^{-6}\exp(0.003x)$ ($R^2 = 0.944$)	285.562 / 0.000**	x (16.899)	0.000**	3.93%
					constant (1.035)	0.031*	

Notes: AWD, IWD and DWD represent water withdrawals in the agricultural, industrial, and domestic sectors, respectively; FIRGDP, SECGDP and TOPOP indicate agricultural GDP, industrial GDP, and total population. * and ** denote significance at $P < 0.05$ and $P < 0.01$, respectively; all values for *S.E.* are less than 15%

(e.g., water withdrawal per GDP or population), can be obtained at a provincial level for the period 1978–1997. These figures can also be used as county-level water coefficient for agricultural, industrial and domestic sectors to estimate water withdrawals at the county level for the same period. This is because we cannot obtain water coefficient of agricultural, industrial and domestic water demands at this administrative level due to data for amounts of water withdrawal not available at this level.

1) Agricultural water withdrawal modelling

Agricultural water withdrawal accounts for an important percentage of global and national water withdrawal structure. It includes water needed for irrigation, fisheries, and animal husbandry. Here we focus on irrigation water withdrawal within the Huaihe River watershed.

$$AWD_{agr}(t) = Area(t) \cdot \alpha_{arg}(t) \tag{1}$$

where $AWD_{agr}(t)$ is the water withdrawal by agricultural sector (in 10^8 m^3), $Area(t)$ is effective irrigation area (in 10^3 ha), and $\alpha_{arg}(t)$ represents water withdrawal per 10^3 ha (water coefficient). The effective irrigation area is the area of cultivated land that can be irrigated normally in the current year with the available water sources and irrigation engineering facilities.

2) Industrial water withdrawal modelling

Water withdrawal modelling for industrial sector is more complicated because this sector includes various industrial categories with different production processes and equipment. Accordingly, different industrial sectors have different water withdrawals. It is difficult to simulate water withdrawal in each industrial sector if detailed data for each industrial sector is not available or not recorded by the statistics department (Blackhurst et al., 2010). Therefore, we use the industrial water use coefficient to simulate secondary industrial water withdrawal at county level (at a comparable price).

$$IWD_{ind}(t) = \alpha \cdot INDP_{ind}(t) \cdot \alpha_{ind}(t) \tag{2}$$

where $IWD_{ind}(t)$ is the water withdrawal by industrial sector (in 10^8 m^3); $INDP_{ind}(t)$ is the secondary GDP value (in 10^8 yuan); α indicates the proportion of industrial output value in secondary GDP, and $\alpha_{ind}(t)$ represents water withdrawal per ten thousand yuan (water coefficient in 10^8 m^3 per 10^4 yuan).

3) Domestic water withdrawal modelling

A close positive correlation exists between domestic water withdrawal and population. Domestic water withdrawal can be modelled according to Equ. 3:

$$DWD_{dom}(t) = Pop(t) \cdot \alpha_{dom}(t) \tag{3}$$

where $DWD_{dom}(t)$ is the water withdrawal of domestic sector (in 10^8 m^3), $Pop(t)$ is the total population (in 10^4 persons), and $\alpha_{dom}(t)$ represents water withdrawal per ten thousand persons (water coefficient in 10^8 m^3 per 10^4 persons).

4) Total water withdrawal

Total water withdrawal is the sum of the volumes of agricultural, industrial, and domestic water. Then water withdrawal per square kilometer equals the total water withdrawal divided by the administrative area.

$$\begin{aligned} Total(t) = & Area(t) \cdot \alpha_{agr}(t) + \alpha \cdot INDP_{ind}(t) \cdot \alpha_{ind}(t) + \\ & Pop(t) \cdot \alpha_{dom}(t) \end{aligned} \tag{4}$$

where $Total(t)$ is the total quantity of water withdrawal (in 10^8 m^3), and the meanings of the other parameters are the same as those in Equs. 1–3.

(2) Water withdrawals at county level in the Huaihe River watershed

Data for water withdrawals at county level are extremely difficult to obtain because most of relevant departments of water resources have not reported or published them, especially before the 1990s. Therefore, corresponding water coefficient cannot be estimated, and there is also very little information and research on water withdrawals at this local administrative level.

In this study, we use the water coefficients for agricultural, industrial, and domestic sectors at provincial level multiplied by corresponding GDP or population to simulate water withdrawals at county level according to existing socio-economic statistical data. There is still a lot of data for socio-economic indicators in some counties that could not be recorded, especially in 1978–1999. Therefore, a regression analysis method (passed test of significance) is used to interpolate the missing data to obtain complete time-series information on population, GDP, and other factors. Then, we take the agricultural sector as an example from which to model water withdrawal with equation 5. Industrial and domestic water withdrawals at county-level can also be estimated in a similar way.

$$\begin{cases} AWD_{agrco}(t_i) = Area_{co}(t_i) \cdot \alpha_{agrco}(t_i) \\ Area_{co}(t_i) = \alpha \cdot Area_{co}(t_{i+1}) + \beta \\ \alpha_{agrco}(t_i) = \alpha_{agrpr}(t_i) \end{cases} \tag{5}$$

where $AWD_{agrco}(t_i)$ is the water withdrawal for agricultural sector in year i (in 10^8 m^3), $Area_{co}(t_i)$ and $Area_{co}(t_{i+1})$ are the effective irrigation areas (in 10^3 ha) in years i and i+1, respectively, and $\alpha_{agrco}(t_i)$ represents water withdrawal per thousand hectares (water coefficient); $\alpha_{agrpr}(t_i)$ is provincial-level water coefficient; t_i is time; α and β are parameters.

(3) Global Moran's I and Getis-Ord G_i^* statistic

Global Moran's I is a correlation coefficient that measures the overall spatial autocorrelation of data set for total water withdrawal (Rogerson, 1999; Zhang and Zhang, 2007), and Getis-Ord G_i^* statistic is used to analyze hot spot or cold spot identification of spatial pattern for water withdrawal (Getis and Ord, 1992; Ord and Getis,1995).

3 Results

We used the methods presented in Section 2 to model the water withdrawals in the Huaihe River watershed during 1978–2018. Fig. 2a depicts the time trend of water withdrawals in this watershed. The percentage composition changes of water withdrawals among agricultural, domestic, and industrial sectors were also displayed from 1978 to 2018 in Fig. 2b.

According to Fig. 2a, the total water withdrawal increased rapidly from 1978 to 2009, and then dropped slowly during 2009–2018. In the same period, the time trend of agricultural water withdrawal was similar to that of the total water use, increasing from 1978 to 2009, and decreasing from 2009 to 2018. Industrial and domestic water withdrawals were constantly growing in 1978–2018. Agricultural water withdrawal was the main water-use sector with an obvious characteristic of structural water withdrawal in the Huaihe River watershed. Fig. 2b shows the percentage composition of water withdrawals from agricultural, domestic, and industrial sectors in 1978–2018. The water withdrawal in agricultural sector accounted annually for more than 60% of the total water withdrawal during the whole period. The percentage of agricultural water accounting for the total withdrawal equaled nearly 72.76%, remaining barely changed from 1978 to 2000, but obviously decreasing to 59.88% in 2018. On the contrary, domestic and industrial water withdrawals accounted for nearly 40% throughout the study period, which is less than that of agricultural sector. In the industrial sector, the percent-

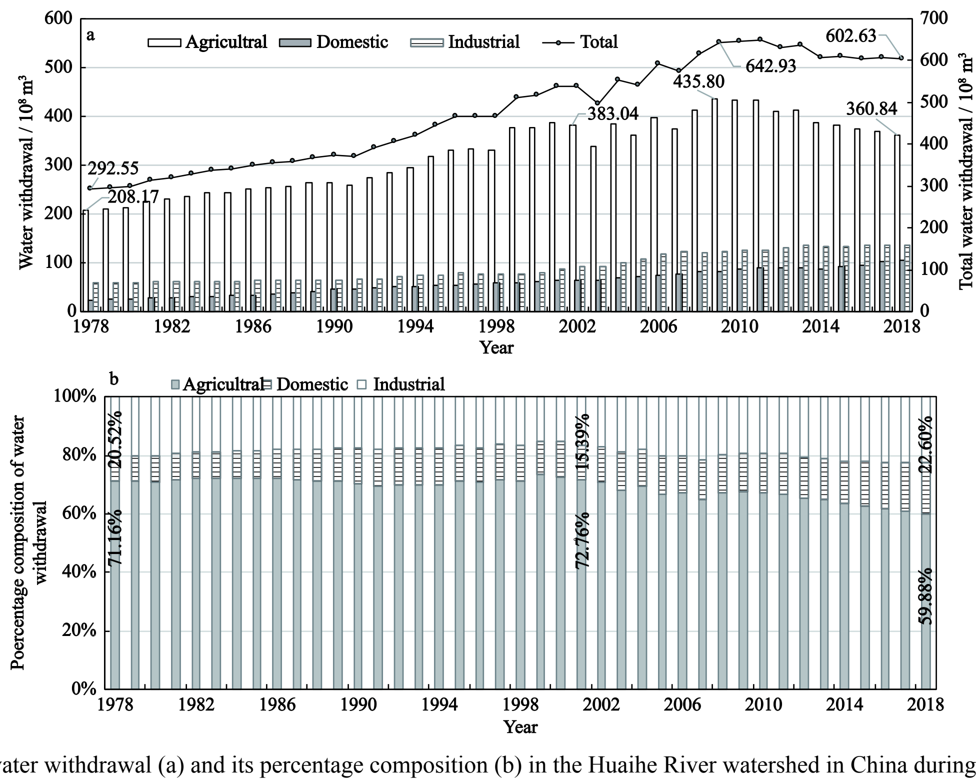

Fig. 2 Total water withdrawal (a) and its percentage composition (b) in the Huaihe River watershed in China during 1978–2018

age of total water withdrawals decreased gradually from 20.52% in 1978 to 15.39% in 2000, but increased to 22.60% in 2018. Domestic water withdrawal increased gradually from 8.32% in 1978 to 17.52% in 2018, nearly doubling over the whole watershed area. At the same time, the population increased significantly from 145 million in 1978 to 222 million in 2018.

3.1 Water withdrawals for agricultural, industrial, and domestic sectors at county-level

According to the results of time-series for water withdrawals in Table 2, agricultural water accounts for the largest percentage of total water withdrawals among the 212 counties in the Huaihe River watershed. On the whole, Table 2 shows that the average agricultural water withdrawal increased before 2010 and decreased after 2010 at county-level. The time trends of the median and difference between mean and median for agricultural water withdrawal are similar to that of its mean for the same period. This showed that the differences in agricultural water withdrawals amongst each county gradually increased and then dropped. On the contrary, the mean for industrial water withdrawal continuously increased from 1978 to 2018, hence doubling. However, the median of industrial water use increased from 1978 to 2010, and dropped during 2010–2018. The difference between mean and median of industrial water use continuously increased and this indicated that industrial water use varied greatly among counties. The time trends of the mean and median for domestic water withdrawal were similar in 1978–2018. The difference between mean and median of domestic water withdrawal became small before 2000, but increased after 2000 among various counties. This showed that there existed a greater variability in domestic water use amongst 212 counties during 1978–2000, but the difference became smaller from 2000 to 2018.

Box plots of water withdrawals showed increasing/decreasing trends of water withdrawals for the agricultural, industrial, and domestic sectors in Fig. 3, where data distribution characteristics of water withdrawals in 212 counties were well illustrated for each year. The distribution (minimum, maximum, and median values) of agricultural water withdrawal in the 212 counties was greater from 1978 to 2010 (Fig. 3a), but was lessening in 2010–2018. Minimum and maximum values of industrial water withdrawals were greater throughout 1978–2018 (Fig. 3b), however, median values in industrial water use remained unchanged from 1978 to 2005, and increased during 2010–2018. Minimum, maximum, and median values of domestic water withdrawal became greater with increasing population from 1978 to 2018 (Fig. 3c). We also found that the distributions of domestic and industrial water withdrawal were different to that of agricultural water withdrawal in 212 counties in the Huaihe River watershed throughout 1978–2018. Fig. 3b and Fig. 3c also showed us that the ranges for water quantity in industrial and domestic sectors were increasing within various counties as the differences in water withdrawals increased among counties for the same period. The range in water quantity in the agricultural sector increased from 1978 to 2010 in Fig. 3a, but

Table 2 The mean and median of water withdrawals for agricultural, industrial, and domestic sectors throughout the watershed during 1978–2018 (10^8 m^3)

Indicator	1978	1980	1985	1990	1995	2000	2005	2010	2015	2018
Mean_AWD	4.841	4.946	5.685	6.128	7.396	8.764	8.391	10.072	8.907	8.392
Median_AWD	3.614	3.722	3.650	4.083	4.745	6.649	5.804	7.329	6.621	6.215
Difference (Mean–Median)	1.227	1.224	2.035	2.045	2.651	2.115	2.587	2.743	2.286	2.177
Mean_IWD	1.396	1.408	1.461	1.526	1.712	1.854	2.535	2.902	3.121	3.168
Median_IWD	1.087	1.086	1.106	1.168	1.265	1.279	1.270	1.545	1.460	1.401
Difference (Mean–Median)	0.309	0.322	0.355	0.358	0.447	0.575	1.265	1.357	1.661	1.767
Mean_DWD	0.566	0.618	0.760	1.062	1.254	1.427	1.678	2.015	2.164	2.455
Median_DWD	0.565	0.617	0.779	1.069	1.278	1.337	1.569	1.867	1.906	2.099
Difference (Mean–Median)	0.001	0.001	–0.019	–0.007	–0.024	0.09	0.109	0.148	0.258	0.356

Notes: Mean_AWD, Mean_IWD and Mean_DWD represent the mean of agricultural, industrial and domestic water withdrawals, and Median_AWD, Median_IWD and Median_DWD indicate the median of agricultural, industrial and domestic water withdrawals. IWD in the industrial sector is calculated at a comparable price

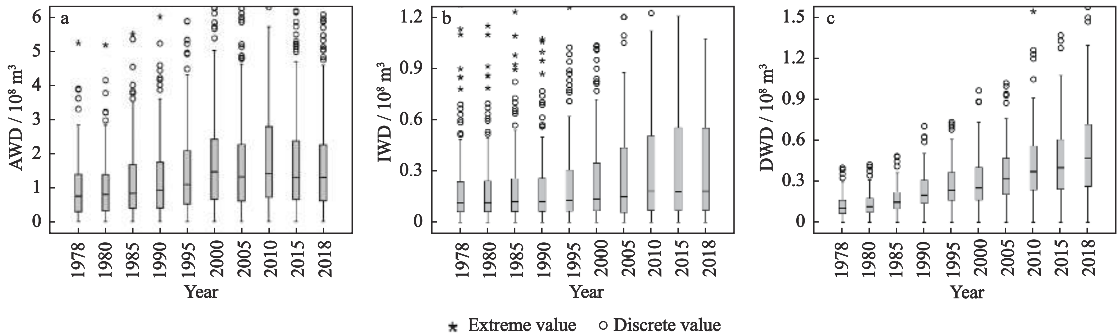

Fig. 3 Box plots of water withdrawals among the agricultural, industrial, and domestic sectors in the Huaihe River watershed in China during 1978−2018

decreased throughout 2010–2018. This could be due to greater differences in agricultural water demand between the various counties before 2010 and lesser differences after 2010.

3.2 Spatial distribution of water withdrawals at county level

The emphasis on the spatial distribution of water withdrawals could reveal information about the actual disparities across the whole study area. With already measured global spatial autocorrelation (Global Moran's *I*), we detected the historical development of water withdrawals in 1978–2018, as shown in Fig. 4. A positive spatial autocorrelation with high values of the Moran's *I* leads to increased clustering of similar values throughout the watershed, with a negative Moran's *I* indicating a clustering of dissimilar values. Fig. 4 shows that Moran's *I* increased from 0.27 in 1978 to 0.36 in 2010, and rapidly dropped to 0.27 in 2018 at county level. This showed that the spatial agglomeration of total water demand has enhanced at county-level in the Huaihe River watershed during 1978–2010, and then weakened from 2010 to 2018.

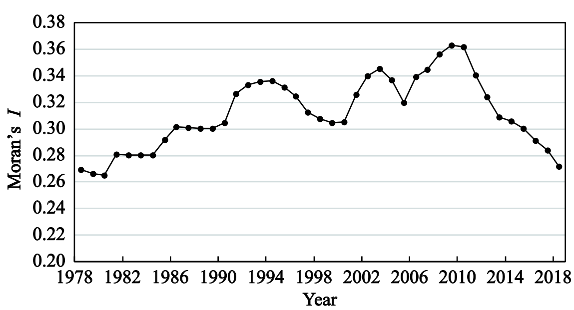

Fig. 4 Spatial agglomeration of total water withdrawal at county-level administrative unit in Huaihe River watershed in China during 1978–2018 (all *P* values of Moran's *I* < 0.01)

We also examined the spatial distribution of total water withdrawal at county-level with a hot spot analysis (Getis-ord G_i^*) to help explicitly recognize the clustering of spatial patterns in 1978–2018. The results of the Getis-ord G_i^* statistic are shown in Fig. 5 which reveals the types of clustering and corresponding locations. Hot spots were mainly concentrated in the southeast area of the Huaihe River watershed for the period 1978–1990. This includes the counties in the southern Jiangsu and the central Anhui provinces. By contrast, cold spots of total water withdrawal were mainly concentrated in the northwest area of the Huaihe River watershed, which includes the counties in the Henan Province (Figs. 5a−5d). Throughout 1995–2005, hot spots shifted to the southeast of the Huaihe River watershed, which includes some counties in Jiangsu Province. The scope of the cold spot was expanded from most of the counties in Henan Province to some parts of Shandong Province (Figs. 5e−Fig. 5g). From 2010 to 2018, the hot spots of the clustering moved from parts of Jiangsu Province to some counties of the northern Anhui Province. Cold spots were still concentrated in some counties of the Henan and Shandong provinces with decreasing confidence (Figs. 5h−Fig. 5j).

4 Discussion

The water resources currently available have become a restraining factor for economic and social development across the globe. There are many regions where available freshwater cannot meet society's needs, thus reducing economic growth and human well-being. Credible estimates of water withdrawals on a detailed scale are particularly important for implementing operational plans to allocate water resources amongst various ad-

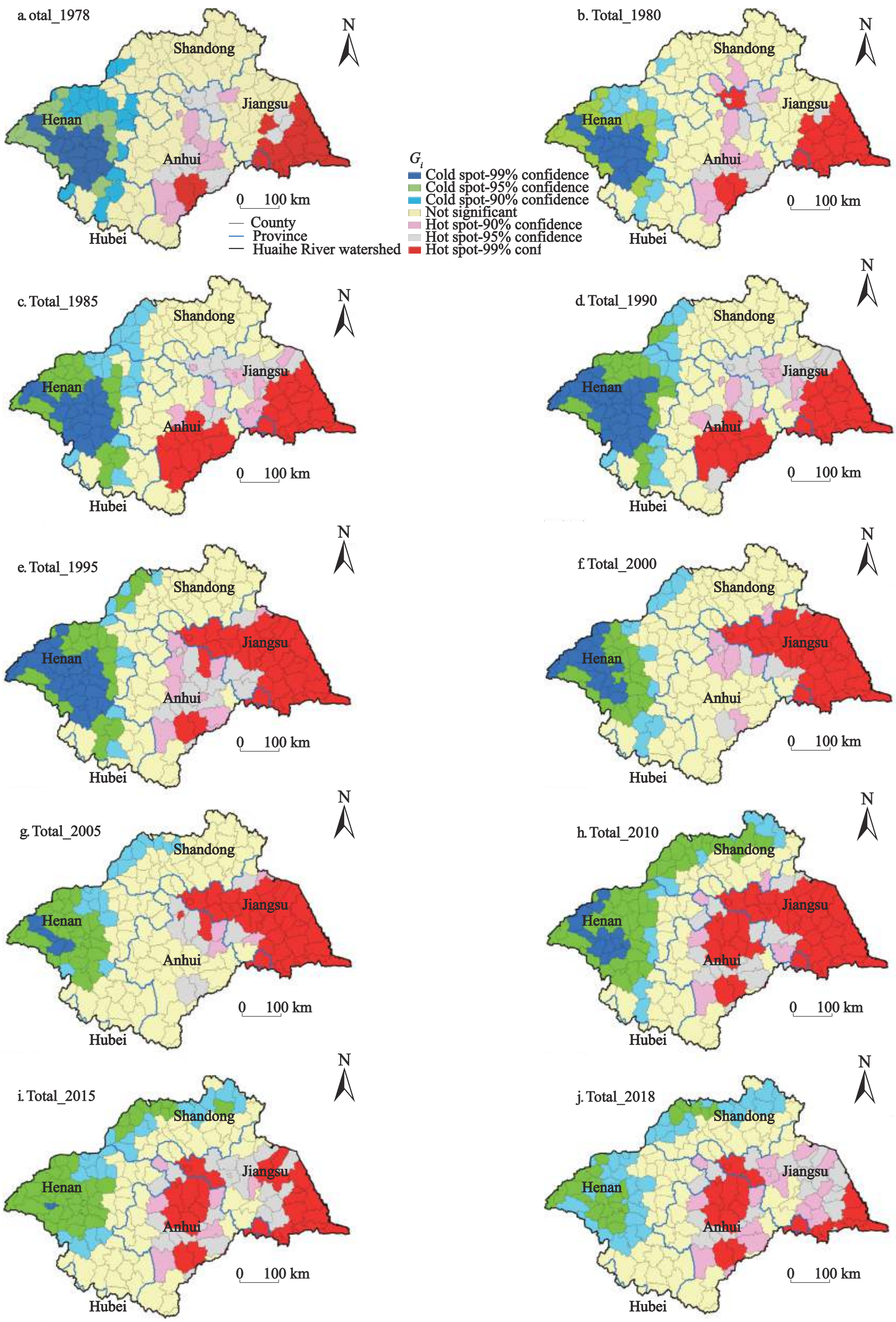

Fig. 5 Spatial distribution of total water withdrawal for a county-level administrative unit in the Huaihe River watershed in China during 1978–2018

ministrative units in response to water shortage. However, there exist few consensuses amongst scientists on how to deal with missing historical water-use data and to use various data sources and methods in estimating water withdrawals at some time-spans, resulting in incredible outcomes. Then, a data-driven framework is proposed here to straighten out different data sources and corresponding data-induced methods to gain credible data for water withdrawal at county-level scale. Additionally, missing historical data for statistical water use at a county-level scale are an important challenge with a data-driven framework to estimate water use.

Most previous studies concentrated on water demands or withdrawals within the agricultural, industrial, and domestic sectors on global, national, and city-level scales using statistical methods such as water coefficient, geographically weighted regression, and water footprint (Chapagain and Hoekstra, 2008; Li et al., 2019; Sanchez et al., 2020). These studies focused mainly on cross-sectional city-level data sets (Flörke, 2018; Zhang et al., 2020c) or roughly global-scale data (D'Odorico et al., 2020) to estimate agricultural, industrial, and domestic water demands for the current years. Unfortunately, there were few studies involving water demand estimation from earlier years due to the required data not being available. Historically, this resulted in insufficient information on water withdrawals to enable policymakers at all levels to gain an understanding of the historical development of water withdrawal on a county or watershed scale. These historical data contain important information on which to base proper decisions for improving water management. The greatest advancement outlined in this article has been the examination of historical changes to water withdrawals over a local scale, which provides base information to enable a deeper understanding of available water resources and water scarcity.

Socio-economic statistical data from human activities provides a valuable basis from which to estimate water withdrawals, especially when they have not been reported by the relevant government authorities. These selected indicators used in modelling water withdrawals are population, GDP, irrigation area and so on, which can be traced back to previous research (Alcamo et al., 2007; Liu et al., 2017). However, irrigation area here refers to the effective irrigation region which can be typically irrigated using available water sources and irrigation infrastructure for the current years. The reason for choosing this indicator is that water withdrawal modelled by using an effective irrigation area is generally more in line with real-world circumstances, and smaller than that modelled by using cultivated land area. A certain amount of arable land around the globe cannot be irrigated due to a lack of sufficient irrigation infrastructure and available water resources (Gohar et al., 2015; D' Odorico et al., 2020). Another problem is that we eliminated the effect of price on secondary output value when calculating industrial water withdrawal. This is used to help understand the historical development of water withdrawal and to detect key drivers of water stress on a local scale.

There is much concern on how to offer highly accurate and reliable results when we evaluate water demand or withdrawal based on data from disparate sources and different models. Various model selection and data uncertainty from missing data such as GDP and population amongst different economic sectors are also important factors that affect the accuracy of water demand simulation (Alcamo et al., 2003; Blackhurst et al., 2010; Ma, 2012). One limitation of our study is that uncertainty exists in water withdrawal evaluation when modelling water withdrawals for agricultural, industrial, and domestic sectors in the Huaihe River watershed. The main problem is that there is a lot of missing data for water withdrawals at the county level. Compared to industrial and domestic water withdrawal estimation, agricultural water demand or irrigation water withdrawal is subjected to more advanced modelling due to various data-driven demands or criteria with different water demand patterns (Niswonger, 2020). Therefore, it is not helpful to reach common consensus amongst scientists on data-driven water demands, and results show low efficiency in directing practical water management. Consequently, agricultural water withdrawal estimation should be studied more deeply to help detect spatio-temporal development at a regional-to-global scale according to a common research framework, e.g., theoretical water demand, actual water consumption or available water withdrawal with sufficient water transfer infrastructure. Then, under this framework, various methods can be chosen to model water demand on global-, national- or local level, e. g., the water coefficient, the Penman-Monteith formula, and the Water GAP model (Mekonnen and Hoekstra, 2011; Döll et al., 2012). The applicable conditions of different models, e.g., data requirements and specific research objectives, should also be concerned furtherly when we determine to conduct a study of water demand evaluation.

Another limitation is that the environmental water requirements were not captured as we could not obtain time-series statistical data for environmental water withdrawals for the study area. Additionally, we are still a long way from an adequate understanding of the differences and competition between agro-economic and environmental water demands (Mccartney et al., 2009; Xue et al., 2016; Flörke et al., 2018). For example, setting the operational threshold of environmental water requirements is still challenging, and this new research field requires interdisciplinary knowledge from ecological, hydrological, and geographical sciences (Yang et al., 2005; Zhang et al., 2020b). Further studies could focus on the theories and methodologies needed to estimate environmental water requirements in river systems and urban/rural areas.

5 Conclusions

This research examined the current situation and existing problems of changes to water withdrawals and their spatial variability in estimating the quantity of global- or nation-scale water demand. Using the Huaihe River watershed in China as an example, this study provided improved and detailed information on water withdrawal within the agricultural, industrial, and domestic sectors on a smaller county-level scale. The findings also revealed that the total water withdrawal increased in 1978–2010, but declined from 2010 to 2018 with various spatial distribution patterns for the same period.

A data-driven framework has been proposed here to help guide a scientific assessment of water demand or water withdrawal according to data availability. It has an advantage for identifying water withdrawal patterns at county-level scale in various time spans, especially when statistical data for water withdrawal are not available. The findings from this framework can be to easily connected with related socio-economic data at county-level administrative unit, even municipal administrative unit, to implement water allocation plan for departments of water resources management. Under this framework, various results can be compared to assist with extensive data and in-depth critical evaluation and to deeply understand the key drivers of water shortage. This article also provided a first examination on the historical development and spatial distribution of the total water withdrawal from the Huaihe River watershed at a county-level using spatial statistical methods such as box plots, Moran's I and Getis-ord G_i^* statistics for the 1978–2018 period. Box plots of water use revealed the differences in water withdrawals between agricultural, industrial, and domestic sectors in 212 counties in the Huaihe River watershed, and their increasing trends of water withdrawals for the period 1978–2018. By comparison, agricultural water withdrawal increased from 1978 to 2010, but declined throughout 2010–2018. The findings of the Moran's I statistics showed that the total water withdrawal represented significant spatial autocorrelation. The overall trend observed was a gradual increase infrom 1978 to 2010 and a decline throughout 2010–2018. The results of the Getis-Ord G_i^* statistics showed spatially contiguous clusters of total water withdrawal in the Huaihe River watershed. The hot spot clustering locations with high values concentrated in the eastern counties and cold spots with low values in the western counties, which could be due, to some extent, to economic disparities and differences in population distribution.

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